

An Automated Text Categorization Framework based on Hyperparameter Optimization

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Abstract

The amount of textual data generated in environments such as social media, blogs, online newspapers, and so on, have attracted the attention of the scientific community in order to automatize and improve several tasks that were manually performed such as sentiment analysis, user profiling, or text categorization, just to mention a few. Fortunately, several of these activities can be posed as a classification problem, i.e., a problem where one is interested in developing a function, from a set of texts with associated labels, capable of predicting a label given an unseen text. In this contribution, we propose a text classifier, named μ TC. μ TC is composed of a number of easy to implement text transformation, text representation and a machine learning algorithm that produce a competitive classifier even over informal written text when these parts are correctly configured. We provide a detailed description of μ TC along with an extensive experimental comparison with the relevant state-of-the-art methods. μ TC was compared on 30 different datasets obtaining the best performance (regarding accuracy) in 18 of them. The different datasets include several problems like topic and polarity classification, spam detection, user profiling and authorship attribution. Furthermore, it is important to comment that our approach allows the usage of the technology even for users without knowledge of machine learning and natural language processing.

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1 Introduction

Due to the large and continuously growing volume of textual data, automated text classification methods have taken an increasing research community interest. Although many efforts have been proposed in this direction, it stills remains as an open problem. The arrival of massive sources of data, like micro-blogging platforms, introduce new challenges where many of the prior techniques failed. Among the new challenges are the volume and noisy nature of the data, the shortness of the texts that imply few context, the informal style also plagued of misspellings and lexical errors.

Along with traditional text classification applications (such as *topic classification*, *authorship attribution* and *spam detection*), these new data sources, also make popular another tasks, like *sentiment analysis* and *user profiling*. Given the content of an e-mail, the spam detection task determines, if the message is relevant or it is an undesired message. The topic classification task consists in predict the topic of a given text, for example, a news-like text can be classified to talk about sports, politics, or economy. The authorship attribution task consists in, given a document and a set of possible authors, the algorithm determines which of them wrote this document, mainly based on its stylistic selection of words and sentences. The sentiment analysis problem consists in determining the polarity of a given text, which can be a global polarity (about the whole text) or about a particular subject. The user profiling task consists in, given a text, predicting some facts about the author, like her/his demographic information (i.e., gender or age). Such is the importance of these problems that in the research community several international competitions are carried out in recent years. For example SemEval¹, TASS² and SENTIPOLC³ are challenges for sentiment classifiers for Twitter data in English, Spanish, and Italian languages, respectively. PAN⁴ also open calls for author profiling systems for English, Spanish and German languages. Usually, each of these problems is treated in a particular way, i.e., a method is proposed to solve adequately one classification task. This approach commonly cannot generalize, and the methods are dependent on the problem; however, it is worth to mention that this kind of work produces a lot of insight about a domain.

This manuscript is organized as follows. Section 2 describes our contribution in depth. We show an extensive experimental comparison of our approach with the relevant state-of-the-art methods over 32 different benchmarks in Section 4. Finally, the conclusions are listed in Section 5.

1.1 Text Classifiers Anatomy

The core algorithm solving the above tasks is the text classifier. A typical text classifier can be summarized as a set of few, but large, parts [1]. The input text

¹<http://alt.qcri.org/semeval2017/>

²<http://www.sepln.org/workshops/tass/2016/tass2016.php>

³<http://www.di.unito.it/~tutreeb/sentipolc-evalita16/>

⁴<http://pan.webis.de/>

is passed to a lexical analyzer that both parse and normalize the text, it outputs a list of tokens that represents the input text. The lexical analyzer typically includes some simple transformation functions like the removal of diacritic symbols and lower casing the text but also can make use of sophisticated techniques like stemming, lemmatization, misspelling correction, etc. The tokens are commonly represented by words, pairs or triplets of adjacent words (bigrams or trigrams), and in general, sequences of words (word n-grams). It is also possible to extend this approach to sequences of characters (character n-grams). When it is allowed to drop the middle words of word n-grams, we obtain skip-grams. The usage of these techniques is driven by the human knowledge of the particular problem being tackled. Also, it is worth to mention that the entire process is tightly linked to the input language.

The output of the lexical analyzer is commonly used to create high dimensionality vectors where each token of the vocabulary has a corresponding coordinate of the vector. So, the value of each coordinate is associated with the weight of that token. The traditional way to weighting is to use the local and global statistics of tokens, popular examples of this approach are *TF*, *IDF*, *TFIDF*, and Okapi BM25; alternatively, some information measures like the entropy are commonly used as weight terms. These approaches are independent of the language. Many times is desirable to reduce the dimension of the vector space, and several techniques can be used for that purpose, just like *PCA* [2] (Principal Component Analysis), and *LSI* [3] (Latent Semantic Indexing).

The resulting matrix of the training set is finally learned by a classifier. A classifier is a machine learning algorithm that learns the instances of a training set \mathbb{T} . More detailed, the training set is a finite number of inputs and outputs, i.e., $\mathbb{T} = \{(x_i, y_i) \mid i = 1 \dots n\}$ where x_i represents the i -th input, and y_i is the associated output. The objective is to find a function ψ such that $\forall_{(x,y) \in \mathbb{T}} \psi(x) = y$ and that could be evaluated in any element x of the input space. In general, it is not possible to find a function ψ that learns \mathbb{T} , perfectly. Consequently, a good classifier finds a function ψ that minimizes an error function or maximizes a score function.

The learning problem has two main tasks, *regression* and *classification*. In this contribution, we focus on the *classification* task, where the co-domain of ψ is a relatively small set of categorical values \mathcal{L} , dubbed as labels. Depending on the number of values of \mathcal{L} , the problem is called binary classification problem ($|\mathcal{L}| = 2$) or a multi-class classification problem (larger \mathcal{L}). There exist many classifiers, like Naïve Bayes, K-Nearest Neighbors (kNN), Support Vector Machines, Artificial Neural Networks (ANN), etc. A proper study of the alternatives is detailed in [4, 5].

The objective of a classifier is to maximize a score function that measures the quality of the predictions; for instance, some of most popular functions are

the following:

$$\begin{aligned}
\text{accuracy} &= \frac{\text{total TP} + \text{total TN}}{\text{total samples}} \\
\text{precision}_c &= \frac{\text{TP}_c}{\text{TP}_c + \text{FP}_c} \\
\text{recall}_c &= \frac{\text{TP}_c}{\text{TP}_c + \text{FN}_c} \\
F_{1,c} &= \frac{2 \cdot \text{accuracy}_c \cdot \text{recall}_c}{\text{accuracy}_c + \text{recall}_c} \\
(\text{micro or macro})\text{-}F_1 &= \sum_{c \in \mathcal{L}} w_c \cdot F_{1,c} \\
w_c &= \begin{cases} \text{macro} \rightarrow 1/\mathcal{L} \\ \text{micro} \rightarrow \frac{|\{u \in \mathcal{D} | u=c\}|}{|\mathcal{D}|} \end{cases}
\end{aligned}$$

Here, TP denotes the number of true positives, TN the true negatives; FP and FN are the number of false positives and false negatives, respectively. All these measures can be parametrized by class c . The *accuracy* is calculated by dividing the total of correctly classified samples by the total number of samples. The $F_{1,c}$ is defined as the harmonic mean of the *precision* and the *recall*, per class. Finally, the average over all classes is simply named F_1 . When the weights are uniform, no matter the population of each class, the measure is known as macro- F_1 ; when the weights are given by the population of each class, the measure is named micro- F_1 . The interested reader is referenced to an excellent survey on text classifiers and performance metrics [6].

1.2 Related work

Our contribution is a framework for modeling generic text classifiers; that means, we expect raw text as input. This approach let us be both language and domain independent. In the following paragraphs, we briefly survey the related state of the art. Lately on §4 we compare the performance of our approach with the related alternatives matching our comparison criteria, also stated in §4.

Rocchio [7] introduces a generic text classifier algorithm that works generating object prototypes based on centroids of a Voronoi partition over *TFIDF* vectors. This strategy clearly shows the effort to reduce the necessary memory to fit on the available hardware of the epoch. Rocchio uses nearest neighbor classifiers over prototypes to perform the predictions, the preprocessing of the text was left to the expertise of the user. Rocchio was the baseline and the study object in the area for a long time; such is the case of the work presented by Joachims [8], which presents a probabilistic analysis of the Rocchio algorithm.

With the purpose to improve the quality of the text classification task, Cardoso [9] proposes the use of centroids to enhance the classification power of

several classical classifiers, such as kNN (k-nearest neighbors) and SVM (Support Vector Machines). Also, Cardoso published a number of datasets in several preprocessing stages, which are popular among the text classification community because using them allow to focus on the weighting and classification algorithms, avoiding to tackle the text processing problem.

There are works focusing on a specific task achieving good results, such as the case of spam identification. In [10] is presented a deep analysis on machine learning methods to construct an effective anti-spam method. The proposed method is based on the combination of a set of features, pre-processing steps or setup details, such as using lemmatization or not, using stop-list or not, keywords patterns, varying the length of the training corpus, etc. A similar work is presented by Androutsopoulos et al. in [11]. In the topic classification task, [12] presents an experimental scheme with the Reuters dataset and three machine learning methods (Rocchio algorithm, k-NN, and SVM) and three-term selection functions (information gain, chi-square and gain ratio). In [13] is proposed a topic modeling algorithm based on Latent Dirichlet Allocation (LDA) which assign one topic to an unlabeled document. Moreover, a combination of LDA and Expectation-Maximization (EM) algorithm is also proposed.

Another approach to text classification is to move the focus from text processing and text classification to improve the term weighting; this is a successful strategy followed by recent works. Cummins [14] proposes a method based on Genetic Programming to determine and evaluate several term weighting schemes for the vector space model.

Escalante et al. [15] presents an approach to improve the performance of classical term-weighting schemes using genetic programming. Their approach outperforms standard schemes, based on an extensive experimental comparison. The authors also compare the Cummins [14] approach over their benchmarks.

Lai et al. [16] use both recurrent and convolutional neural networks to produce a term-weighting scheme that captures semantics from the text. Similarly to word embeddings [17, 18], the authors represent words based on their context and, also, they use skip-grams for text representation. The experimental results show higher values of macro-F1 in comparison with other state-of-the-art methods.

Vilares et al. [19] introduce an unsupervised approach for multilingual sentiment analysis driven by syntax-based rules; the words are weighted based on the analysis of syntax-graphs. The authors provide experimental support for English, Spanish, and German. However, to support a new language, it needs to implement several rules for that language, and a proper syntax parser for the language.

Mozetič et al. [20] study the effect of the agreement among human taggers in the performance of sentiment classifiers. In this way, they compare several classifiers over a traditional text normalization and a vector representation with *TFIDF* weighting. They provide 14 tagged datasets for European languages; we selected some of them for our benchmarks. See §4 for more details.

In [21], we present a combinatorial framework for sentiment analysis named B4MSA. There, we consider aspects of the language like stopwords and tokeniz-

ers, and with special attention to lexical structures for negations. Also, particularities of the domain like *emoticons* and *emojis* are considered. The presented manuscript is a generalization and formalization of our previous work; this allows us to simplify the entire framework to work independently of both the language and the particular task, and empower the use of more sophisticated text treatments whenever it is possible and necessary.

2 The Proposed Approach

As stated above, we tackle the problem of creating text classifiers that work regardless of both the domain and the language, with nothing more than a training set to be learned. The general idea is to orchestrate a number of simple text transformations, tokenizers, a set of weighting schemes, along with an SVM classifier to produce effective text classification. More detailed, we look to state the problem of creating effective text classifiers as a combinatorial optimization problem; in particular, each possible combination of the parts (models) compose the configuration space. Then, a meta-heuristic that solves the combinatorial problem is used to obtain highly effective text classifiers. The model selection procedure is many times named in the literature as *hyper-parameter optimization*. To emphasize the simplicity of the approach, we named it *micro* Text Classification or, simply, μ TC.

2.1 A Combinatorial Framework for Text Classification

As detailed in §1.1, a text classifier consists a well differentiated parts. We go beyond in the segmentation to simplify each part: i) a list of functions that normalize and transform the input text to the input of tokenizers, ii) a set of tokenizer functions that transform the given text into a multiset of tokens, iii) a function that generates a vector from the multiset of tokens; and finally, iv) a classifier that knows how to assigns a label to a given vector.

To create a classifier, μ TC needs to know the set of possible operations in a structured manner. The idea is to find the best configuration among all possible text classifiers setups in the space. The definition of a μ TC space is given by the tuple $(\mathcal{F}, \mathcal{G}, \mathcal{H}, \mathcal{L})$; each part is defined as follows:

1. We define $\mathcal{F} = \{F_i\}$ as the space of transformation functions, where F_i is defined as the identity function I and a set of related functions, mutually exclusive.⁵ We define the function $f(S) = (f_{|\mathcal{F}|} \circ \dots \circ f_1)(S)$ such that $f_i \in F_i$. Please notice that the context is enough to distinguish between the set F_i and the score function F_1 .
2. $\mathcal{G} = \{G_i\}$ is the set of tokenizer functions. Each G_i is defined as either a function that returns \emptyset or a simple tokenizer function, i.e., a tokenizer function is a function that extracts a list of subsequences of the given

⁵The identity function is defined as $I(S) = S$.

argument. More precisely, the function $g(S) = g_1(S) \cup \dots \cup g_{|\mathcal{G}|}(S)$ is defined; where g_i extracts a list of subsequences of S . The final multiset is named as *bag of tokens*.

3. $\mathcal{H} = \{h_i\}$ is a set of functions that transform a bag of tokens v into a vector \vec{v} of dimension d , i.e., $h : S^+ \rightarrow \mathbb{R}^d$ where $S \in \Sigma^+$. The proper value of each coordinate is also determined by h ; the later task is commonly known as *weighting scheme*.
4. Finally, $\Psi = \{\psi_i\}$ is a set of functions that create a classifier for a given labeled dataset.

Now, let \mathcal{C} be the set of all possible configurations of the μ TC space; therefore, it is defined as follows:

$$\mathcal{C} = F_1 \times \dots \times F_{|\mathcal{F}|} \times G_1 \times \dots \times G_{|\mathcal{G}|} \times \mathcal{H} \times \Psi$$

then, the size of \mathcal{C} is described by

$$|\mathcal{C}| = \left(\prod_{i=1}^{|\mathcal{F}|} |F_i| \right) \cdot 2^{|\mathcal{G}|} \cdot |\mathcal{H}| \cdot |\Psi|.$$

Without loss of generality, the size of the search space can be summarized as $(2 + O(1))^{|\mathcal{F}|+|\mathcal{G}|} \cdot |\mathcal{H}| \cdot |\mathcal{L}|$, where the $O(1)$ term captures the effect of F_i s with more than two member functions. This means that $|\mathcal{C}|$ is lower bounded by $2^{|\mathcal{F}|+|\mathcal{G}|}$, i.e., all F_i s are binary and both \mathcal{H} and \mathcal{L} are singletons. Even on the simplest setup, the configuration space grows exponentially with the number of possible transformations and tokenizers. Thus, to find the best item it is necessary to evaluate the entire space, this is computationally not feasible.⁶ A typical configuration space can contain billions of configurations such that the exhaustive evaluation is not feasible in current computers. To remain as a practical approach, instead of performing an exhaustive evaluation of \mathcal{C} to find the best configuration we relax the problem to find a (very) good configuration; then it can be solved as a combinatorial optimization problem, in particular, as the maximization of a **score** function.

To solve the combinatorial problem it is necessary to create a graph where the vertex set corresponds to \mathcal{C} , and the edge set corresponds to the neighborhood of each vertex, $\{N(c) \subseteq \mathcal{C}^+ \mid c \in \mathcal{C}\}$. The edges are simply denoted by the neighborhood function N , so (\mathcal{C}, N) is a μ TC graph.

Our main assumption is simple and feasible, the function **score** slowly varies on similar configurations, such that we can assume some degree of *locally concaveness*, in the sense that a local maximum can be reached using greedy decisions at some given point. Even when this is not true in general, the solver algorithm should be robust enough to get a good approximation even when the

⁶For instance, evaluating each configuration takes about 10 minutes on a commodity workstation; more about this will be detailed in the experimental section.

assumption is valid only with some degree of certainty. To induce the search properties, the neighborhood N should be defined in such a way that neighborhoods describe only similar configurations. For this matter, we should define a distance function between configurations. On the first hand, we must define a comparison function,

$$\Delta(a, b) = \begin{cases} 1 & \text{if } a \text{ and } b \text{ are the same function} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Since each configuration is a tuple of functions, the Hamming distance over configurations is naturally defined as follows

$$d_H(u, v) = \sum_{i=1}^{|\mathcal{F}|+|\mathcal{G}|+2} \Delta(u_i, v_i). \quad (2)$$

Now, we can define $N(c, r_{\max}) = \{u \in \mathcal{C} \mid 0 < d_H(u, c) \leq r_{\max}\}$, for any r_{\max} and a configuration c . However, the number of items grows exponentially with the radius, and therefore, the notion of locality will be rapidly degraded. To maintain the locality, we define the neighborhood as:

$$N(c) = \{u \in \mathcal{C} \mid d_H(c, u) = 1\}. \quad (3)$$

Under this construction scheme, the diameter of (\mathcal{C}, N) is determined by the length of the configuration tuple, i.e., $O(\log |\mathcal{C}|)$, the diameter determines the number of hops in the μ TC graph that an optimal **opt** algorithm will perform, in the worst case. However, since the best configuration is unknown, we must use *score* as an *oracle* that leads our navigation at each step. A typical *score* function measures the quality of the expected results, e.g., F1 (macro or micro), accuracy, precision or recall (mentioned above) [6].

The algorithms that navigate (\mathcal{C}, N) correspond to combinatorial optimization algorithms. There exist several metaheuristics to solve combinatorial optimization problems, the proper survey of the area is beyond the scope of this manuscript; however, the interested reader is referred to [22, 23].

To maintaining μ TC in practical computational requirements, we select two types of fast meta-heuristics, *Random Search* [24] and *Hill Climbing* [22, 23] algorithms. The former one consists in randomly sampling \mathcal{C} and select the best configuration among that sample. Given a pivoting configuration, the main idea behind Hill Climbing is to explore the configuration's neighborhood and greedily move to the best neighbor. The process is repeated until no improvement is possible. We improve the whole optimization process applying a Hill Climbing procedure over the best configuration found by a Random Search. We also add memory to avoid a configuration to be evaluated twice⁷. Without loss of generality, the evaluation of a configuration $c \in \mathcal{C}$ can be described by three main steps:

⁷In principle, this is similar to Tabu search; however, our implementation is simpler than a typical implementation of Tabu search.

1. the dataset \mathcal{D} is divided into D_{train} and D_{test} .
2. the μTC algorithm described by c learns from D_{train} .
3. the prediction performance of c is evaluated with `score` using the dataset D_{test} .

These steps can be implemented in a slightly more sophisticated way to support cross-validation schemes like k -folds or bagging.

The optimization process is driven by the tuple $(\mathcal{C}, \mathcal{D}, \text{score}, \text{opt})$, where i) \mathcal{C} is the μTC space, ii) \mathcal{D} means for the training set of labeled texts, iii) `score` is the function to be maximized, and finally, iv) `opt` is a combinatorial optimization algorithm that uses `score` and \mathcal{D} to find an almost optimal configuration in \mathcal{C} .

3 Experimental Setup

This section describes the general setup used to characterize and compare our method with the related state-of-the-art. In particular, we define the set of functions used to create our μTC space; and also, we detail the benchmarks used in the comparison.

All the experiments were run in an Intel(R) Xeon(R) CPU E5-2640 v3 @ 2.60GHz with 32 threads and 192 GiB of RAM running CentOS 7.1 Linux. We implemented μTC ⁸ on Python. To characterize the performance of μTC and compare with the relevant state of the art, we select a number of popular benchmarks in the literature; these datasets are described below. It is worth to mention that we bias our selection to benchmarks coming from popular international challenges. With the purpose of avoiding over-fitting, we perform the model selection using `score` as a 3-fold cross-validation of the specified performance measure, see Table 1. We decide to use cross-validation for this stage because we observed over-fitting for small datasets, like those found in authorship attribution, when we use a static train-test partitions to perform model selection. A brief experimental study of the effect of the validation schemes is presented in §4.2.

3.1 About the μTC Space

As commented, μTC is a framework to create text classifiers searching for best models in a configuration space. This space can be adjusted for any particular problem, but here, we consider a general enough space to match a disparity of benchmarks (listed below in §3.3).

When the knowledge about the domain is low, then a large and generic configuration space should be used. It could be tempting to learn about the domain using the information found by the optimization process; this is clearly possible. However, it is encouraged to take into account that the search process will take decisions to match the particular dataset, not the domain, and any

⁸Available under Apache 2 license at <https://github.com/INGEOTEC/microTC>

generalization of the knowledge must be curated by an expert in the domain. It is worth to mention that large configuration spaces will consume a lot of computational time to be optimized.

On the other hand, a hand-crafted configuration space for a given problem can yield to very fast processing times; however, a vast knowledge of the domain is required to reach this state. In this case, we discard the possibility of discovering new knowledge on the domain and take advantage of the particularities of the dataset that a more general configuration space can provide.

To tackle with the disparate list of benchmarks, we select a generic large configuration space defined in the following paragraphs.

Preprocessing functions $\mathcal{F} = \{F_1, \dots, F_{|\mathcal{F}|}\}$ We associate F_i to the following function sets.

hashtag-handlers. Defined as $\{remove_htags, group_htags, identity\}$, the idea is to allow to remove or group into a single tag all hash tags, for *remove_htags* and *group_htags*, respectively; the *identity* function lets the text unmodified. The format of a hash tag is that introduced by Twitter *#words*, but now popular along many data sources.

number-handlers. Defined as $\{remove_num, group_num, identity\}$, this function set contains functions to remove, group, or left untouched numbers in the text.

url-handlers. Defined as $\{remove_urls, group_urls, identity\}$, this function set contains functions to remove, group, or left untouched numbers in the text.

usr-handlers. Defined as $\{remove_usr, group_usr, identity\}$, this function set contains functions to remove, group, or left untouched users and host domains in the text. The pattern being tackled is *@user* this is a popular way to denote users in several social networks; the pattern also matches naturally with the domain part of email addresses.

diacritic-removal. Defined as $\{remove_diac, identity\}$, this function set contains functions to remove, or left untouched, diacritic symbols in the text. The objective is to reduce composed symbols like *á, â, ã, ä*, or to simply *a*. This is a well known source of errors in informal text written in languages making hard use of diacritic symbols

duplication-removal. Defined as $\{remove_dup, identity\}$, this function set contains functions to remove, or left untouched, duplicated contiguous symbols in the text.

punctuation-removal. Defined as $\{remove_punc, identity\}$, this function set contains functions to remove, or left untouched, duplicated punctuation symbols in the text. The list of punctuation symbols includes several symbols like *;, : , . , - , ' , " , (,) , [,] , { , } , ~ , < , > , ? , ! ,* among others.

lower-casing. Defined as $\{lower_case, identity\}$ contains functions to normalize the case of the text or left untouched.

The list of tokenizers $\mathcal{G} = \{G_1, \dots, G_{|\mathcal{G}|}\}$ After all text normalization and transformation, a list of tokens should be extracted. We use three schemes for our tokenizers.

Word n-grams. This family of tokenizers firstly tokenizes the text into words, and then, produce $m - n + 1$ tokens for m words, i.e. word n -grams. An n -gram is a string of n consecutive words. For example, “The red car is in front of the tree” creates the following 3-grams: The red car, red car is, car is in, is in front, in front of, front of the, of the tree.

Character n-grams. This family of tokenizers does not assume anything about the text and splits the input text to all n -sized substrings, i.e., $m - n + 1$ substrings of characters for a text of m characters. For example, the character 4-grams of “I like the red car” are I_li, _lik, like, ike_, ke_t, e_th, _the, the_, he_r, e_re, _red, red_, ed_c, d_ca, _car. We use the symbol _ to show the symbol space.

Skip-grams. Skip-grams are similar to word n-grams but allowing to *skip* the middle parts. For example, the $(2, 1)$ skip-grams⁹ of the previous example are I-the, like-red, the-car. The idea behind this family of tokenizers is to capture the occurrence of related words that are separated by some unrelated words.

For this matter, instead of selecting one or another tokenizer scheme, we allow to select any of the available tokenizers, and perform the union of the final multisets of tokens. For instance, our configuration space considers three word n-grams tokenizers ($n = 1, 2, 3$), nine character n-grams ($n = 1..9$), and three skip-grams $(3, 1)$, $(2, 2)$, and $(2, 1)$.

Weighting schemes \mathcal{H} . After we obtained a multiset (bag of tokens) from the tokenizers, we must create a vector space. We selected a small set of frequency filters and the TFIDF scheme to weight the coordinates of the vector. On the one hand, we consider a sequential list of filters **max-filter** and **min-filter**, and then, we select to use the term frequency (TF) or the TFIDF as weight. For the **max-filter** we delete all tokens surpassing the frequency threshold of $\alpha \text{max-freq}$, where **max-freq** is the maximum frequency in of a token in the collection. We consider four filters, for instance we use $\alpha \in \{0.9, 0.95, 0.99, 1.0\}$. For the **min-filter** we delete all tokens not reaching the frequency threshold of $freq$, for instance we use, $freq \in \{1, 3, 5, 10\}$. Notice that $\alpha = 1.0$ and $freq = 1$ does not perform any filtering. So, we have embedded 32 different configurations for weighting.

Classifier Ψ We decide to use a singleton set populated with an SVM with a linear kernel. It is well known that SVM performs excellently for very large dimensional input (which is our case), and the linear kernel also performs well under this conditions. We do not optimize the parameters of the classifier since

⁹Two words, skipping one in the middle

we are pretty interested in the rest of the process. We use the SVM classifier from *liblinear*, Fan et al. [25].

On the final configuration space The task of finding the best model for the space of configurations is hard. The number of possible configurations of \mathcal{F} is 1296 (i.e., four trivalent functions sets and four bivalent function sets). From the above configuration, the number of possible tokenizers is 81; also, we have 32 different weighting combinations. So, the configuration space contains more than 3.3 million configurations. For instance, a configuration needs close to ten minutes to be evaluated, i.e., a sentiment analysis benchmark with ten thousand tweets. Therefore, an exhaustive evaluation of the configuration space will need up to 64 years. Even implementing in a large distributed cluster the process needs too much time to complete. Such power of computing is not easily accessible. Nonetheless, if we relax the problem to finding not the best model but an excellent one, we can use an algorithm for combinatorial optimization, as explained in §2.1.

3.2 On the preparation of the input text

Since μ TC considers the preprocessing step among its parts, we tried to collect all datasets in raw text, without any kind of preprocessing transformations. This was not possible in the general case, mostly due to the aging of datasets; we consider the following text preparation states, in the style of Cachopo [9]:

- the *raw* text corresponds to the original, non-formatted text
- the *all-terms* converts all text into lowercase, also, all diacritic symbols and punctuation marks are removed, and all spacing symbols are normalized to a single space
- the *no-short* dataset removes all terms having less or equal than three characters
- the *no-stopwords* dataset also removes all non discriminant words for English (adjectives, adverbs, conjunctions, articles, etc.)
- finally, after the previous steps, all words were transformed by the Porter’s stemmer for English [26] to generate the *stemmed* dataset.

For instance, we use the *all-terms* for R8, R10, R52 and WebKB; for CADE we use the *stemmed* version. In these cases, we used the datasets prepared by Cachopo [9]. In other cases, we use the raw text. The effect of using one or another state is studied in Section 4.1.

3.3 Benchmark description

The text classification literature has a myriad of datasets, performance measures, and validation schemes. We select several prominent and popular benchmark configurations in the literature; for instance, we select to work with topic

classification, spam identification, author profiling, authorship attribution, and sentiment analysis. To avoid implementation mistakes, we directly use the reported performances by the literature; nevertheless, we are restricted to compare under the same circumstances. Table 1 describes the language and number of classes of each dataset; it also describes the kind of validation; in particular, we consider two validation schemes: i) 10-fold cross-validation, and ii) a static train-test partition of the specified sizes. The diversity of benchmarks and validation schemes help us to prove the functionality of our approach in many circumstances.

The Reuters-21578¹⁰ is one of the most used collection for text categorization research. The documents were manually labeled by personnel from Reuters Ltd. The 20Newsgroup¹¹ dataset is very popular in text classification area and it contains news related to different topics originally collected by Ken Lang. The WebKB dataset¹² contains university webpages. This dataset is composed by the webpages classified in seven different categories: student, faculty, staff, department, course, project and other. We use the four most popular classes in our experiments. The CADE dataset [9] is another collection of webpages, specifically Brazilian webpages classified by human experts. This collection contains a total of 12 classes, e.g. services, sports, science, education, news, among others. The PU [11] is a collection of emails written in English and other languages, classified as spam and non-spam messages; this collection contains the following datasets: PUA, PU1, PU2 and PU3. Ling-Spam dataset [27] is also a spam dataset. PAN contest [28, 29] has several task, between them are author identification and author profiling. The author profiling task is a forensic linguistics problem, i.e., detecting gender and age for the author. The task of author identification is that given a document should be identified who wrote it. The Authorship Attribution datasets [15] are a set of different types of topics: CCA, NFL, Business, Poetry, Travel and Cricket. The objective of these datasets is to determine the authorship of each document. The Multilingual Sentiment Analysis are a set of tweets in different languages: Arabic, German, Portuguese, Russian, Swedish and Spanish. The purpose of these datasets is classifying each tweet as negative, neutral, or positive polarity.

A detailed description of all these datasets is given by Table 1, where it can be found some particularities of the dataset like the written language, the number of documents, the kind of evaluation (independent train-test sets or k -folds), the number of classes, and the performance measure optimized by μ TC.

4 Experimental Results

This section is dedicated to comparing our work with the relevant state-of-the-art methods described above. Also, we characterize the generalization power in terms of the validation scheme.

¹⁰<http://www.daviddlewis.com/resources/testcollections/reuters21578/>

¹¹<http://people.csail.mit.edu/jrennie/20Newsgroups>

¹²<http://www.cs.cmu.edu/~webkb/>

Table 1: Description of the benchmarks and its associated performance measure

name	language	# documents			# classes	performance measure
		total	train	test		
Topic classification						
R8	English	7,674	70%	30%	8	macro-F1
R10	English	8,008	70%	30%	10	macro-F1
R52	English	9,100	70%	30%	52	macro-F1
News-4	English	13,919	70%	30%	4	macro-F1
News-20	English	20,000	70%	30%	20	macro-F1
WebKB	English	4,199	70%	30%	4	macro-F1
CADE	Portuguese	40,983	70%	30%	12	macro-F1
Spam identification						
Ling-Spam	English	2,893	— 10-fold —		2	macro-F1
PUA	English [†]	1,142	— 10-fold —		2	macro-F1
PU1	English [†]	1,099	— 10-fold —		2	macro-F1
PU2	English [†]	721	— 10-fold —		2	macro-F1
PU3	mixed [†]	4,139	— 10-fold —		2	macro-F1
PAN 2013						
Age group	English	242,040	236,600	25,440	3	accuracy
Gender	English	242,040	236,600	25,440	2	accuracy
Age group	Spanish	84,060	75,900	8,160	3	accuracy
Gender	Spanish	84,060	75,900	8,160	2	accuracy
PAN 2016 [‡]						
Age group	English	428	— 10-folds —		5	accuracy
Gender	English	428	— 10-folds —		2	accuracy
Age group	Spanish	250	— 10-folds —		5	accuracy
Gender	Spanish	250	— 10-folds —		2	accuracy
Authorship Attribution						
CCA	English	1000	500	500	10	macro-F1
NFL	English	97	52	42	3	macro-F1
Business	English	175	85	90	6	macro-F1
Poetry	English	200	145	55	6	macro-F1
Travel	English	172	112	60	4	macro-F1
Cricket	English	158	98	60	4	macro-F1
Multilingual Sentiment Analysis						
Arabic	Arabic	2,000	— 10-folds —		3	macro-F1
German	German	91,502	— 10-folds —		3	macro-F1
Portuguese	Portuguese	86,062	— 10-folds —		3	macro-F1
Russian	Russian	69,100	— 10-folds —		3	macro-F1
Spanish	Spanish	19,767	— 10-folds —		3	macro-F1
Swedish	Swedish	49,255	— 10-folds —		3	macro-F1

[†] these datasets are encoded in a way that the original text is loss, however it preserves the document's distribution.

[‡] here, the documents are Twitter's profiles, each user is described by around 1000 tweets.

The first task analyzed is authorship attribution, Table 2 shows the macro-F1 and accuracy performances for a set of authorship attribution benchmarks. Here, we compare μ TC with two term-weighting schemes [15] and [14]. The pre-processing stage of the μ TC’s input is *all-terms*; others use the *stemmed* stage. The best performing classifiers are created by μ TC, except for NFL where alternatives perform better. In the case of **Business**, Escalante et. al [15] performs slightly better only in terms of accuracy. Please notice that NFL and **Bussiness** are among the smaller dataset we tested, the low performance of μ TC can be produced by the low number of exemplars, while alternative schemes take advantage of the few samples to compute better weights.

Table 2: Authorship Attribution Data sets

Dataset	macro-F1			Dataset	Accuracy		
	Cummins [14, 15]	Escalante [15]	μ TC		Cummins [14, 15]	Escalante [15]	μ TC
CCA	0.0182	0.7032	0.7633	CCA	0.1000	0.7372	0.7660
NFL	0.7654	0.7637	0.7422	NFL	0.7778	0.8376	0.7555
Business	0.7548	0.7808	0.8199	Business	0.7556	0.8358	0.8222
Poetry	0.4489	0.7003	0.7135	Poetry	0.5636	0.7405	0.7272
Travel	0.6758	0.7392	0.8621	Travel	0.6833	0.7845	0.8667
Cricket	0.9170	0.8810	0.9665	Cricket	0.9167	0.9206	0.9667

In Table 2 the results of PAN2013 competition are presented. According to the contest report [28], the best results were achieved by Meina and Pastor L. Nevertheless, μ TC produces the best result in all cases except in accuracy metric in Age classification task where Meina obtained the best.

Table 3: Author profiling: PAN2013 competition.

Profiling Aspect	English					
	Meina [28]		Pastor L. [28]		μ TC	
	macro-F1	acc.	macro-F1	acc.	macro-F1	acc.
Age	-	0.6491	-	0.6572	0.4663	0.6605
Gender	-	0.5921	-	0.5690	0.6236	0.5867
Joint	-	0.3894	-	0.3813	0.2801	0.3946
	Spanish					
	Santosh		Pastor L.		μ TC	
	macro-F1	acc.	macro-F1	acc.	macro-F1	acc.
Age	-	0.6430	-	0.6558	0.4661	0.6897
Gender	-	0.6473	-	0.6299	0.6749	0.6750
Joint	-	0.4208	-	0.4158	0.3111	0.4587

The PAN 2016 competition results are shown in Table 4. Here, μ TC produces an accuracy of 0.3925 and a macro-F1 of 0.1661, in tasks of age and gender recognition jointly in Spanish language. In English, similar results are reached. It is important to notice that in PAN 2016 we do not have the gold standard dataset, for this reason, we do not report results of the winner competition work.

Table 5 reports the performance over topic classification benchmarks. This experiments considered several *news* datasets. Please see 1 to get the detailed description of each benchmark. Our approach, μ TC, reaches best results in

Table 4: Author profiling: PAN2016 [29] Data set, k-folds=5.

Profiling Aspect	μ TC			
	English		Spanish	
	macro-F1	acc.	macro-F1	acc.
Age	0.2662	0.4447	0.2236	0.5289
Gender	0.7479	0.7482	0.7313	0.7314
Joint	0.1952	0.3294	0.1661	0.3925

most of the datasets in exception of News-20 and News-4 where μ TC reaches second and third best performance.

Table 5: Topic Classification Datasets

	macro-F1						
	Reuters-8C	Reuters-10C	Reuters-52C	News-4C	News-20C	WebKB	CADE
Debole [12]	-	-	-	-	-	-	-
Escalante [15]	0.9135	0.9184	-	-	0.6797	0.8879	0.4103
Cummins [14, 15]	0.8830	0.8759	-	-	0.6645	0.7197	-
Lai CNN [16]	-	-	-	0.9479	-	-	-
Lai RNN [16]	-	-	-	0.9649	-	-	-
Hingmire [13]	-	-	-	-	-	0.7190	-
Cachopo [9]	-	-	-	-	-	-	-
μ TC	0.9698	0.9662	0.6746	0.9432	0.8269	0.9098	0.5687
	accuracy						
	Reuters-8C	Reuters-10C	Reuters-52C	News-4C	News-20C	WebKB	CADE
Debole [12]	-	0.7040	-	-	-	-	-
Escalante [15]	0.9056	0.8821	-	-	0.6623	0.8912	0.5380
Cummins [14, 15]	0.7440	0.7659	-	-	0.6578	0.7542	-
Lai CNN [16]	-	-	-	-	-	-	-
Lai RNN [16]	-	-	-	-	-	-	-
Hingmire [13]	-	-	-	0.9360	-	-	-
Cachopo [9]	0.9049	-	0.8482	-	0.8460	0.8300	0.5071
μ TC	0.9214	0.9236	0.9376	0.9390	0.8348	0.9191	0.6174

In sentiment analysis task we compared the datasets reported in [30, 31]. Moreover, we reported the results obtained with the B4MSA approach [32]. B4MSA is a method for multilingual polarity classification considered as a baseline to build a more complex approaches¹³. It is important to note that from each dataset reported in [30, 31], both approaches, B4MSA and μ TC use a subset specified in Table 6; e.g. in Arabic language we used 100%, in German we use 80% of the dataset and so on (all specified in table).

In Table 6, it can be seen that best results were obtained with B4MSA and μ TC in all the cases, where can be seen that both results are very close.

Finally, Table 7 shows the results of spam classification task. Here, it can be seen that best results in the macro-F1 measure were obtained with our approach μ TC; nevertheless, the best results in the accuracy score were achieved by Androutsopoulos et al. [33] except in Ling-Spam dataset where μ TC reached the best performance.

¹³<https://github.com/INGEOTEC/b4msa>

Table 6: Multilingual sentiment analysis

language		macro- F_1	accuracy
Arabic	Salameh et al. [30]	-	0.787
	Saif et al. [31]	-	0.794
	B4MSA (100%)	0.642	0.799
	μ TC (100%)	0.641	0.792
German	Mozetič et al. [20]	-	0.610
	B4MSA (89%)	0.621	0.668
	μ TC (89%)	0.614	0.672
Portuguese	Mozetič et al. [20]	-	0.507
	B4MSA (58%)	0.557	0.561
	μ TC (58%)	0.562	0.566
Russian	Mozetič et al. [20]	-	0.603
	B4MSA (69%)	0.754	0.750
	μ TC (69%)	0.754	0.751
Swedish	Mozetič et al. [20]	-	0.616
	B4MSA (93%)	0.680	0.691
	μ TC (93%)	0.679	0.688
Spanish	B4MSA	0.657	0.784
	μ TC	0.649	0.780

4.1 About the pre-processing state of the input text

Here, the pre-processing step is analyzed; for this, Table 8 shows different performances that correspond to the **News** benchmark in various stages of the normalization process, as used as inputs for μ TC. We found that μ TC achieves high performances without using additional sophisticated pre-processing steps, almost all of them, language dependent. For instance, using the raw text is just below 0.0148 points than the performance using the *stemmed* collection. The human intervention to prepare the input text is barely needed by μ TC without significantly reduce the performance in practice. Alternatively, methods like Escalante et al. [15] and Cachopo [9] need to use the stemmed version of the dataset to achieve its optimal performance, i.e., accuracy values ranging from 0.6623 to 0.8460, for more details see Table 5.

4.2 On the robustness of the score function

The **score** function leads the model selection procedure to fulfill the requirements of the task. In this process, it is necessary to determine which precise quality’s measure is needed, e.g., macro-F1 or accuracy; since any learning algorithm is prone to over-fit, it is necessary to protect the **score** with some validation schemes to reduce the latent overfitting. On this matter, we consider the use of two validation schemes: i) stratified k -folds and ii) a random binary partition of size βn for the train set and $(1 - \beta)n$ for the test set, for a (training) collection

Table 7: spam classification

macro-F1				
Data set	Androutsopoulos [33]	Sakkis [34]	Cheng [35]	μ TC
Ling-Spam	-	0.8957	0.9870	0.9979
PUA	0.8897	-	-	0.9478
PU1	0.9149	-	0.983	0.9664
PU2	0.6794	-	-	0.9044
PU3	0.9265	-	0.977	0.9701

accuracy				
Data set	Androutsopoulos [10]	Sakkis [34]	Cheng [35]	μ TC
Ling-Spam	-	-	0.9800	0.9993
PUA	0.9600	-	-	0.9482
PU1	0.9750	-	0.971	0.9706
PU2	0.9839	-	-	0.9634
PU3	0.9778	-	0.968	0.9738

Table 8: The performance of μ TC for text collections being in different stages of text normalization for News benchmark.

kind of preprocessing	actual accuracy	actual macro-F1	pred accuracy	pred macro-F1
raw	0.8265	0.8199	0.8968	0.8963
all-terms	0.8340	0.8260	0.9075	0.9056
no-short	0.8310	0.8235	0.9052	0.9034
no-stopwords	0.8373	0.8300	0.9099	0.9082
stemmed	0.8413	0.8344	0.9071	0.9058

of size n .

To learn how to choose the right criteria, we review both the *predicted* and the *actual* performance (macro-F1, for instance) of these two validation schemes. The predicted macro-F1 is the performance achieved by the model selection procedure using some of the two mentioned validation schemes. The actual performance is the one obtained directly evaluating the gold-standard collection.

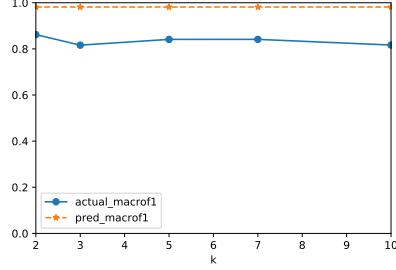
Figures 1 shows the performance of μ TC on small databases. The stability of k -folds in terms of predicted and actual performance is supported by Figures 1(a), 1(c) and 1(e). This is also true for larger datasets like those depicted by Figures 2(a), 2(c) and 2(e). The figures show that even on $k = 2$ the μ TC achieves almost its optimal actual performance; even when the predicted performance is most of the times better for larger k values. On the other hand, the binary partition method is prone to overfit, especially on small datasets and small $1 - \beta$ values (i.e., small test sets). For instance, Figure 1(b) shows the performance for NFL; please note how $\beta = 0.5$ yields to very competitive performances, i.e. higher than 0.9 for both macro-F1 and accuracy. These performances are pretty higher than those achieved by the alternatives (see Table 2); however, $\beta > 0.5$ yields to low actual performances, contrasting the perfect predicted performance. A similar case happens for the Business dataset,

Figure 1(d); but in this case, the actual performance is relatively stable. The behaviour of binary partition in larger dataset is less prone to overfit, like Figures 2(b) and 2(d) illustrate. Nonetheless, the case of R52, Figure 2(f), shows that the overfitting issue is still latent; however, it barely affects the actual performance since the `score` function is applied to a large enough test set.

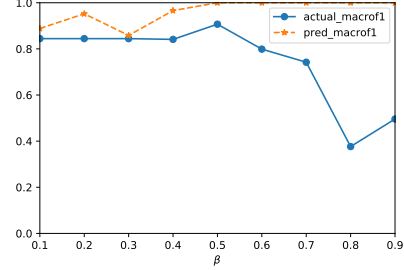
As rule of thumb, it is safe to use k -fold cross-validation to compute `score` in the model selection stage. We encourage the use of small k values (e.g., 2, 3 or 5) since the actual performance is relatively stable and the computational cost is kept low. Please notice that k -folds procedure introduces a factor of k to the computational cost of `score`, and, algorithms to solve the underlying combinatorial optimization problem need to evaluate a considerable number of configurations to achieve good results. In cases where the number of samples is pretty large, or a rapid solution is required, the binary partition method is also a good choice, especially for high $1 - \beta$ values. The later setup corresponds to prepare robust `score` functions at the cost of reducing the train set in the model selection stage. The reduction of the training set is not a major problem for the actual performance, as it is illustrated by experiments corresponding to binary partition performances, see Figures 1 and 2. Please remember, at this stage, we are just selecting a proper configuration, and in a subsequent step, the final model is computed using this configuration and the entire training dataset \mathcal{D} .

5 Conclusions

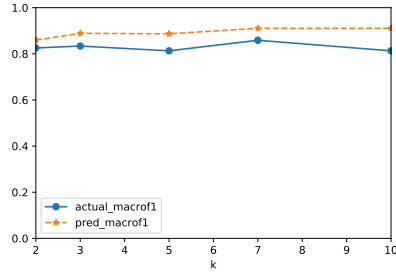
In this work, a minimalistic and global approach to text classification is proposed. Moreover, our approach was evaluated in a broad range of classification tasks such as topic classification, sentiment analysis, spam detection and user profiling; for this, a total of 30 databases related with these tasks were employed. In order to evaluate the performance of our approach, the results obtained in each task were compared with the state-of-the-art methods. Additionally, we analyze the effect of the pre-processing stage. In this experiment, we observed that our approach is competitive with the alternative methods even using the raw text as input, without a penalty in the performance; therefore, it is possible to use μ TC to create text classifiers with a little knowledge of natural language processing and machine learning techniques. We also study some simple strategies to avoid overfitting problem; we consider using a k -fold cross-validation scheme and a binary partition to perform the model selection. Based on our experimental observation, our μ TC can both properly fit the dataset and speedup the construction step using small k values in cross-validation schemes and small training sets when we use binary random partitions. We also found that perform k -folds can be the preferred validation scheme on small to medium sized datasets, but very large datasets can use the binary partition scheme without a significant reduction of the performance, and also, keeping low the cost the entire process.



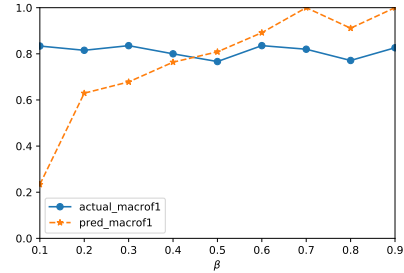
(a) Authors NFL – k-folds



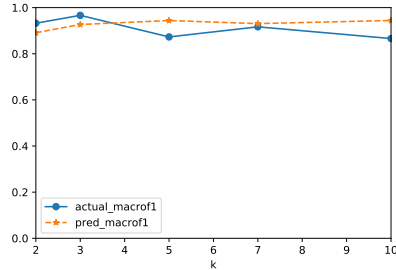
(b) Authors NFL – binary partition



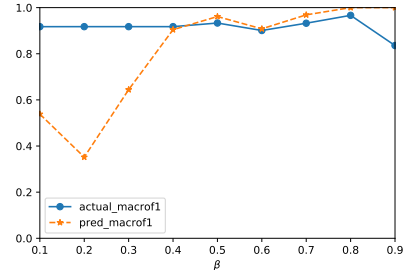
(c) Authors Business – k-folds



(d) Authors Business – binary partition



(e) Authors Cricket – k-folds

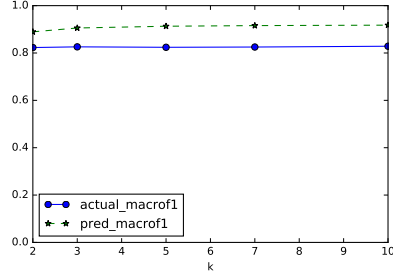


(f) Authors Cricket – binary partition

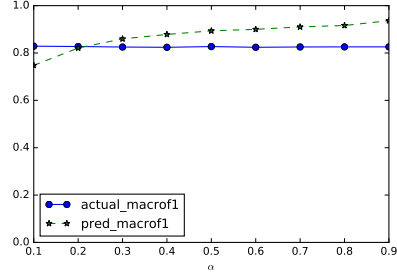
Figure 1: The final performance in small datasets as a function of the validation's stage of the `score` function of μTC ; we consider two validation schemes for this purpose: i) k -folds and ii) random binary partitions of sizes βn and $(1 - \beta)n$, for training and testing subsets respectively.

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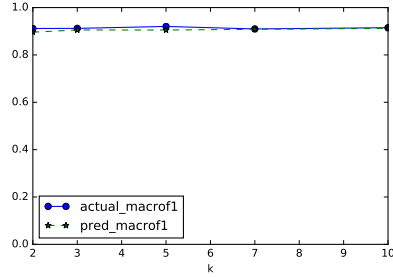
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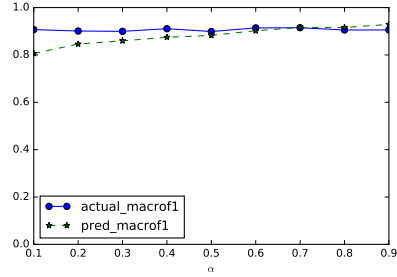
(a) News – k-folds



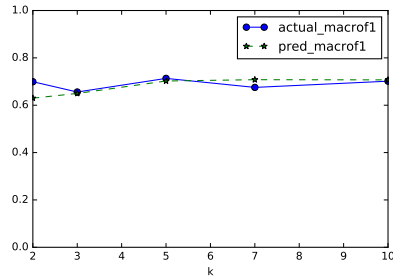
(b) News – binary partition



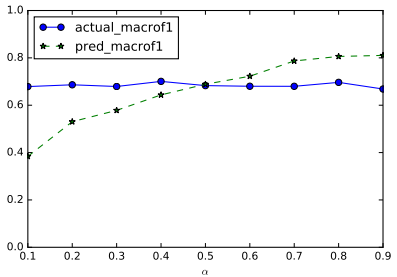
(c) WebKB – k-folds



(d) WebKB – binary partition



(e) R52 – k-folds



(f) R52 – binary partition

Figure 2: The final performance on medium sized datasets as a function of the validation’s stage of the `score` function of μTC ; we consider two validation schemes for this purpose: i) k -folds and ii) random binary partitions of sizes βn and $(1 - \beta)n$, for training and testing subsets respectively.

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